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Extremist Text Post Detection on Social Media: Review

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ABSTRACT

As the numbers of users on social media are increasing day by day, the cases of extremisms on social media are also increasing. Social media provides a convenient way to people where they can share their ideas and beliefs with others. People are using these websites to promote their businesses and spreading news and useful information. Twitter tweets and Facebook posts are also used for opinion mining or sentiment analysis. Extremists are using social media to propagate their beliefs, recruiting new people in their groups, raising funds and planning operations. Extremists groups are misguiding and brain washing people by propagating their ideologies through extremist contents on social media. Social media provides an easy way to them to interact with large number of people without physically present there. They use sophisticated techniques to outwit the automated extremist post detection system. We reviewed the work of other researchers and presented in this paper who worked on this problem or other problems which are similar to this problem.

KEYWORDS: *cyberbullying, hate speech, extremism, machine learning based methods, social media*

I. INTRODUCTION

People have found Internet as convenient and cheapest way of communication. They can connect and interact with large number of people with ease on social media. It is very common to find people sharing new ideas and information with unknowns on Internet. Social media has changed the lifestyle of people. Most of the time people seek information on Internet due to the ease of availability of Internet. Trisha [7] specified that social media is capable of changing social life. Antoci et al[8] specified that with social media people can connect with others without any barrier of distance. They suggested by social media one can grow his network and make it strong offline also. The power of Internet and social media can be used for constructive purposes as well as for destructive purposes also. Social media is a powerful tool. Extremists can easily connect with like-minded people or their supporters on social media. These like-minded people support extremists and their ideology by sharing their contents and making it viral so that they can influence other like-minded people and strengthen their network.

McKenn and Bargh[1] in their research describe that for terrorists motives Internet is being used by terrorist groups. Tsfati and Weimann [2] described that Internet is being used to brain wash vulnerable people by terrorist groups. Klausen et al [3] discovered that YouTube was used by extremists for propaganda. They discovered how YouTube was being used for terror network creation. Klausen[4] discovered that extremist groups are representing them more powerful than reality on twitter. Cristina et al [5] argued that the way of thinking of a person can be flipped by repeated messaging and terrorist organizations are using social network for recruitment purposes. Natascha and Ute [6] concluded in their study that human brain is affected by social media and specified the need of interaction on social media to be sensible.

Effects of social media on society and individuals are described by Natascha and Ute [6]. They concluded that social media has both advantages and disadvantages at the same time. They also argued that by false identity someone can misbehave online.

Naveen and Sandeep [9] suggested that on social media extremism can appear in many forms like personal insult, use of abusive language. George et al [10] analyzed Twitter content which was suspended and found that Twitter accounts which were related to terrorism had many different characteristics. They concluded the possibility of automatic detection of Twitter accounts involved in activities related to terrorism.

II. LITERRATURE REVIEW

Social media websites have been proved boon for terrorist organizations not only for propagating their ideology but also for planning their operations and recruiting new terrorists [11]. There is a need for an automated hateful speech detection system on social media.

Johnston[12] explored different types of terrorism and he manually compiled a dataset for each type of terrorism and prepared it for binary classification. He compared the performance of Long Short Term Memory units (LSTMs) and logistic regression for text classification. He got average accuracy of 88% for his model. Ryan and Richard[13] collected 20000 webpages and classified them into five classes: no extremism, radical Right, radical Islamic, anti-extremist and new source discussing extremism. They found frequent keywords and calculated sentiment values for them for every webpage and then they applied decision tree with calculated sentiment values.

Asif et al[14] used machine learning algorithms as well as multilingual lexicon based sentiment analysis methods. They created multilingual lexicon with intensity weights. Lexicon attained 88% accuracy and among machine learning based classifier linear support vector classifier attained maximum accuracy of 82%. They had classified the texts into four categories: high extreme, low extreme, moderate and neutral.

Ahmad et al [15] classified tweets into extremist and non-extremist by sentiment analysis technique based on deep-learning. They got good results of experiments. For one – class classification Swati and Ashish[16] used a single class SVM and KNN algorithm. They did case study on Jihad. They got F-score for KNN 0.60 and for SVM classifier 0.83. Salminen et al[17] collected 197,566 comments from various platforms. They labeled 80% of them as non-hateful and remaining were labeled as hateful. They experimented with various classification algorithms like Logistic Regression, XGBoost, Neural Network, Naïve Bayes and support vector machine and feature representations. Their results shown that XGBoost performed the best using all the features. They found BERT features as the most impactful.

Gaydhani et al[18] classified tweets into three classes: clean, offensive and hateful. They used multiple machine learning models and got 95.6% accuracy. In their experiment they used n-gram and TFIDF based approach. Diaset et al[19] did experiment to filter racist comments. They trained a support vector machine with facebook comments which were labeled as racist and non racist. Their model achieved 70% accuracy. Pereira et al[20] presented an intelligent system HaterNet. Spanish National Office Against Hate Crimes of the Spanish State Secretariat for Security is currently using HaterNet. HaterNet identifies hate speech on twitter. They introduced a Spanish dataset of 6000 tweets. Tweets in dataset were labeled by experts. Several classification approaches were compared by them. They found the combination of LSTM+MLP neural network as the best approach.

Researchers encountered some challenges also while detecting hateful speeches on social media. MacAvaney et al [21] described challenges in hate speech detection. They described difficulties like subtleties in language, data availability and different definitions of hate speech.

Joshua and Kathleen [22] characterized twitter conversations in U.S. and Philippines about the pandemic Covid19. They found relationship between hate speech and bot. They discovered a link between higher hate and bot activity in U.S. and Philippines. Alshalan et al [23] identified hate speech on twitter in Arab region during Covid19 pandemic. They used a dataset which was an ongoing collection of Arabic tweets which are concerning with Covid19. They used Convolution Neural Network (CNN) model.

Owoeye and Weir [24] developed an automated sentiment-based model for the classification of extremist websites which did classification with 93% accuracy.

Jacob and Matthew [25] suggested methods for recruitment activity detection on extremist social media websites. Methods suggested by them used supervised learning techniques and natural language processing (NLP). They suggested that it is feasible to automatically detect online activity of recruitment of terrorists. For detecting OEC (online extremist community) Matthew et al [26] suggested IVCC (iterative vertex clustering and classification) method.

Kaled et al [27] proposed a SVM based system to detect content on Twitter which is related to terrorism.

B. Sentiment Analysis

The techniques used for sentiment analysis can be used for extremist text post detection. Sentiment analysis is a field of natural language processing. Sentiment analysis is popularly also known as opinion mining. The general purpose of sentiment analysis is to automatically classify a text as neutral, positive or negative. In sentiment analysis sentiments, opinions and attitude are analyzed through the texts. Sentiment analysis is usually done to know the sentiments and opinion of people towards a particular entity. Opinion of people towards the policies of government may be helpful for a political party to design its strategies. Opinion of people towards a particular product (positive or negative) may be used by manufacturing companies for making crucial decisions. In this section approaches used for sentiment analysis is discussed as the problem extremist post detection is the problem of classifying a text document as extremist or non-extremist which is quite similar to sentiment analysis in which a text document is classified as positive, negative or neutral on the basis of its meaning.

All the approaches which are used for sentiment analysis can be roughly classified into three categories: machine learning based approach, lexicon based approach and hybrid approach.

Hybrid approach is the combination of both lexicon-based and machine learning based approaches

Lexicon based approach is based on the concept that the polarity of a text document can be found considering the polarity of words of which it consists of [41]. Lexicon-based approach can be divided into two categories: dictionary based approach and corpus based approach [42]. In dictionary based approach first some sentimental words are taken manually to form a seed list and then with the help of dictionaries new words are found which are synonyms and antonyms of seed words. These newly found words are added to the seed list. Same process is repeated until no new words to be added in the seed list are found from the dictionary. In corpus based approach opinion words which are context specific are also identified along with words of seed list [42].

In machine learning based approach machine learning algorithms are used. For sentiment analysis machine learning algorithms have been used in many cases [43]. Machine learning algorithms which are used for general text classification can be employed for sentiment analysis and extremist post detection. Some commonly used machine learning algorithms which can be used for sentiment analysis are decision tree, Naïve Bayes, support vector machine and random forest.

C. Machine Learning Based methods

Classifying social media posts is a problem of text classification. In Text classification, text documents are labeled with classes[28][29]. Machine Learning techniques used for text classification can be divided into three categories: Supervised learning algorithms, Unsupervised Learning algorithms, Semi-supervised Learning algorithms.

Supervised Learning Algorithms for Text Classification: Supervised learning algorithms need to be trained first. For training purpose, already classified data is required. Shweta et al [30] described that K-Nearest neighbor algorithm is easy to implement but it becomes slow with the growth training dataset. Small amount of data is required for Naive Bayes algorithm's training. When Naïve Bayes algorithms applied on large databases high accuracy was received. Drawback of Naïve Bayes is that its performance decreases when dependency exists between assumed features, for high performance assumed features must be independent. Support vector machine is a complex algorithm and requires more memory and time. SVM is an effective method for Text Classification.

Unsupervised Learning Algorithms for Text Classification: For these algorithms we do not need labeled dataset for the training. These algorithms cluster unclassified text documents in such a way that text documents which are in same cluster are more similar to each other than the text document of any other cluster.

Semi-supervised Learning Algorithms: These algorithms use unclassified data and some classified data for predicting the class of new unclassified data.

For detecting hate speech from the online comments Chikashi et al[31] developed a machine learning based method. Kelly et al [32] used C4.5 decision tree learner and an instance based learner for detection of content related to cyberbullying. Bandeh et al[33] developed a solution based on supervised machine learning for detecting cyberbullying and its severity in Twitter. Amgad and Suliman[34] used seven machine learning based algorithm for cyberbullying detection and then compared performance of these algorithms. They used Naïve Bayes, Logistic regression, Stochastic Gradient Descent, AdaBoost, Random Forest, Supprot Vector Machine and Light Gradient Boosting Machine. They got best recall(1.00) by Support Vector Machine and best F1 score (0.928) by Logistic regression. In their experiments they got median accuracy of Logistic regression around 90.57%. Abdhullah and Shahin [35] did experiments for the purpose of detecting social media bullying in Bangla by using various machine learning algorithms. In their experiments support vector machine algorithm performed best. They got 97% accuracy of support vector machine in their experiments.

D. Deep Learning Based Methods

Researchers have used deep learning methods to detect extremism and solving other similar problems like cyberbullying and hate speech detection. After analyzing multilingual hate speech on large scale Sai et al [36] found that simple models performed best in low resource settings whereas performance of BERT based models is better in high resource setting. In their experiments they used these four models: MUSE+CNN-GRU, Translation + BERT, LASER+LR, mBERT.

Pinkesh et al[37] did experiment with deep learning methods on a dataset of 16000 labeled tweets for hate speech detection and found that these methods performed better than char/word n-gram methods. Davdar and Eckert [38] found in their study that deep learning methods performed better than machine based methods for automatic detection of cyberbullying at social network. Seok and Sung [39] proposed a hybrid method which was combination of character level CNN and word level LRCN for detecting cyberbullying.

Andrew and Angjelo[40] used LSTM models for detecting that a given piece of text belongs to which extremist group among four extremist groups: Antifacist groups, White Nationalists, Sunni Islamic and Sovereign citizens. They found their method better than non-deep learning approaches.

E. Performance Metrics for Text Classifiers

To evaluate the performance of text classifier usually these five metrics are used: accuracy, precision, recall, F1 score and ROC/AUC curve. The complete performance of a text classifier can be described by confusion matrix. To understand these concepts one needs to understand about these four terms: true positive (tp), true negative (tn), false positive (fp) and false negative (fn).

True positive (tp) specifies the number of instances of positive class that are correctly predicted as positive by the classifier.

True negative (tn) specifies the number of instances of negative class that are correctly predicted as negative by the classifier.

False negative (fn) specifies the number of instances of positive class that are incorrectly predicted as negative by the classifier.

False positive (fp) specifies the number of instances of negative class that are incorrectly labeled as positive by the classifier

The formula for evaluating the accuracy is

$$Accuracy = \frac{(tp + tn)}{(tp + tn + fp + fn)}$$

Accuracy is the ratio of correctly classified instances to the total number of instances classified.

Precision can be calculated by the formula:

$$precision = \frac{tp}{(tp + fp)}$$

Precision is the ratio of positive class instances which are correctly classified as positive to total number of instances which are predicted as positive by the classifier.

Recall can be calculated the formula:

$$Recall = \frac{tp}{(tp + fn)}$$

Recall is the ratio of positive class instances which are correctly classified by the classifier to the total number of positive class instances.

F1 score which is the harmonic mean of recall and precision can be evaluated by the formula:

$$F1\ score = 2 * \frac{precision * recall}{precision + recall}$$

ROC (receiver operator characteristic) curve is plotted with true positive rate (tpr) against the false positive rate (fpr). AUC is the area under curve which is plotted with true positive rate (tpr) against the false positive rate (fpr). True positive rate is same as recall and false positive rate can be evaluated by the formula

$$false\ positive\ rate(fpr) = \frac{fp}{(fp + tn)}$$

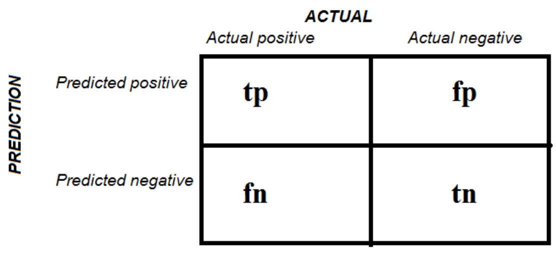

Fig. 1 Confusion matrix

III. CONCLUSION

After reviewing the work of other researchers we concluded that automated detection of extremist post on social media is feasible. There are many approaches for detecting extremist post detection. Datasets required for experimentation are easily available on web.

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